

Influence Maximization in the Field: The Arduous Journey from Emerging to Deployed Application

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ABSTRACT

This paper focuses on a topic that is insufficiently addressed in the literature, i.e., challenges faced in transitioning agents from an emerging phase in the lab, to a deployed application in the field. Specifically, we focus on challenges faced in transitioning HEALER and DOSIM, two agents for social influence maximization, which assist service providers in maximizing HIV awareness in real-world homeless-youth social networks. These agents recommend key "seed" nodes in social networks, i.e., homeless youth who would maximize HIV awareness in their real-world social network. While prior research on these agents published promising simulation results from the lab, this paper illustrates that transitioning these agents from the lab into the real-world is not straightforward, and outlines three major lessons. First, it is important to conduct real-world pilot tests; indeed, due to the health-critical nature of the domain and complex influence spread models used by these agents, it is important to conduct field tests to ensure the real-world usability and effectiveness of these agents. We present results from three real-world pilot studies, involving 173 homeless youth in an American city. These are the *first such pilot studies* which provide head-to-head comparison of different agents for social influence maximization, including a comparison with a baseline approach. Second, we present analyses of these real-world results, illustrating the strengths and weaknesses of different influence maximization approaches we compare. Third, we present research and deployment challenges revealed in conducting these pilot tests, and propose solutions to address them. These challenges and proposed solutions are instructive in assisting the transition of agents focused on social influence maximization from the emerging to the deployed application phase.

1. INTRODUCTION

The process of building a software agent that can be deployed regularly in the real-world to assist under-served communities is very difficult. While significant attention has been paid in the literature to build agents for innovative applications, the topic of transitioning agents from an emerging phase in the lab, to a deployed application in the field, has not received significant attention [8]. This paper illustrates the research challenges and complexities of this topic by focusing on agents for a particular health-critical do-

main, i.e., raising awareness about HIV among homeless youth.

Homeless youth are twenty times more likely to be HIV positive than stably housed youth, due to high-risk behaviors (such as unprotected sex, exchange sex, sharing drug needles, etc.) [3, 5]. To reduce rates of HIV infection among youth, many homeless youth service providers (henceforth just "service providers") conduct peer-leader based social network interventions [17], where a select group of homeless youth are trained as *peer leaders*. This peer-led approach is particularly desirable because service providers have limited resources and homeless youth tend to distrust adults. The training program of these *peer leaders* includes detailed information about how HIV spreads and what one can do to prevent infection. The *peer leaders* are also taught effective ways of communicating this information to their peers [20]. Because of their limited financial and human resources, service providers can only train a small number of these youth and not the entire population. As a result, the selected peer leaders in these intervention trainings are tasked with spreading messages about HIV prevention to their peers in their social circles, thereby encouraging them to move to safer practices. Using these interventions, service providers aim to leverage social network effects to spread information about HIV, and induce behavior change (increased HIV testing) among more and more people in the social network of homeless youth.

In fact, there are further constraints that service providers face – behavioral struggles of homeless youth means that service providers can only train 3-4 peer leaders in every intervention. This leads us to do sequential training; where groups of 3-4 homeless youth are called one after another for training. They are trained as peer leaders in the intervention, and are asked *information* about friendships that they observe in the real-world social network. This newer *information* about the social network is then used to improve the selection of the peer leaders for the next intervention. As a result, the peer leaders for these limited interventions need to be chosen strategically so that awareness spread about HIV is maximized in the social network of homeless youth.

Previous work proposed HEALER [27] and DOSIM [25], two agents which assist service providers in optimizing their intervention strategies. These agents recommend "good" intervention attendees, i.e., homeless youth who maximize HIV awareness in the real-world social network of youth. In essence, both HEALER and DOSIM reason strategically about the multiagent system of homeless youth to select a sequence of 3-4 youth at a time to maximize HIV awareness. While HEALER [27] is an adaptive software agent that solves POMDPs to select the best set of peer leaders, DOSIM [25] uses robust optimization techniques to find the correct set of peer leaders, even when the influence probability parameters are not known. Unfortunately, while earlier research [27, 25] pub-

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lished promising simulation results from the lab, neither of these agent based systems have even been tested so far in the real world. This paper illustrates that transitioning these agents from the lab into the real-world is not straightforward.

Several questions need to be answered before final deployment of these agents. First, do peer leaders actually spread HIV information in a homeless youth social network, and are they able to provide meaningful information about the social network structure during intervention training (as assumed by HEALER and DOSIM)? Second, the benefits of deploying a social influence maximization agent which selects peer leaders needs to be ascertained, i.e., would agents (which use POMDPs and robust optimization approaches to reason about underlying social networks) outperform standard techniques used by service providers to select peer leaders? If they do not, for some unforeseen reason, then a large-scale deployment is unwarranted. Third, which agent out of HEALER or DOSIM performs better in the field? Finally, any unforeseen challenges that arise need to be solved before deployment.

To answer these questions, it is necessary to conduct real-world pilot tests, before deployment of these agents on a large scale. Indeed, the health-critical nature of the domain and complex influence spread models used by social influence maximization agents makes conducting pilot tests even more important, to validate their real-world effectiveness. This paper presents results from three real-world pilot studies, involving 173 homeless youth in an American city. *This is an actual test involving word-of-mouth spread of information, and actual changes in youth behavior in the real-world, as a result.* To the best of our knowledge, these are the first such pilot studies which provide head-to-head comparison of different software agent (with POMDP, robust optimization driven) approaches for social influence maximization, including a comparison with a baseline approach. *Our pilot study results show that HEALER and DOSIM achieve 184% more information spread than Degree Centrality (baseline), and do significantly better at inducing behavior change among homeless youth.* Second, we present analyses of these real-world results, illustrating the strengths and weaknesses of different influence maximization approaches we compare. Specifically, we illustrate how HEALER and DOSIM cleverly exploit the community structure of real-world social networks to outperform Degree Centrality. Third, we present research challenges revealed in conducting these pilot tests, and propose solutions to address them. These challenges dispel any misguided notions about the ease of taking applications from the emerging to the deployed application phase. Finally, the promising results obtained in these pilot studies opens the door to future deployment of HEALER and DOSIM by service providers on a regular basis.

2. MOTIVATING DOMAIN AND RELATED WORK

The nearly two million homeless youth in the United States [23] are at high risk of contracting HIV [15]. Given the important role that peers play in the HIV risk behaviors of homeless youth [18, 7], it has been suggested that *peer leader based interventions* for HIV prevention be developed for these youth [1, 18, 7].

These interventions are desirable for homeless youth (who have minimal health care access, and are distrustful of adults), as they take advantage of existing relationships [19]. These interventions are successful in focusing limited resources to select portions of large social networks [1, 14]. However, there are still open questions about “correct” ways to select peer leaders in these interventions, who would maximize awareness spread in these networks.

Unfortunately, very little previous work in the area of real-world

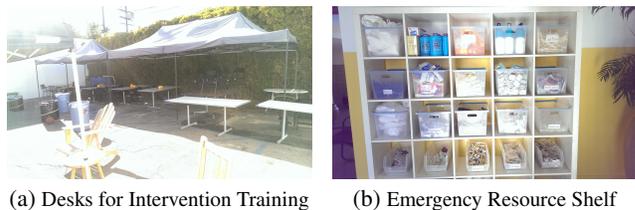


Figure 1: Facilities at our Collaborating Service Providers

implementation of influence maximization has used AI or algorithmic approaches for peer leader selection, despite the scale and uncertainty in the networks; instead relying on convenience selection or simple centrality measures. Kelly et. al. [9] identify peer leaders based on personal traits of individuals, irrespective of their structural position in the social network. Moreover, selection of the most popular youth (i.e., Degree Centrality based selection) is the most popular heuristic for selecting peer leaders [24]. However, as we show later, Degree Centrality is ineffective for *peer-leader based interventions*, as it only selects peer leaders from a particular area of the network, while ignoring other areas. On the other hand, research in computational influence maximization has led to the development of several algorithms for selecting “seed nodes” in social networks [10, 13, 2, 4]. Unfortunately, none of these algorithms has been used for peer-leader based interventions in the real world; as most of them do not handle uncertainties in network structure, and the sequential nature of conducting interventions (ex-cept [6]), both of which are crucial in real-world settings.

Indeed, a key challenge in using sophisticated network based methods for peer leader selection in this domain is that the structure of homeless youth social networks is not known with certainty [20]. Even with rigorous network data collection methods, there is usually uncertainty about the real-world existence of many friendships in the network [19]. This uncertainty and scale of the network implies that choosing peer leaders strategically is extremely difficult for humans; this is where software agents can help. Indeed, previously developed agents like HEALER [27, 28, 26] and DOSIM [25] rely on *observations* about newer friendships to continually refine their understanding of the network, which in turn improves peer leader selection in future interventions. Unfortunately, HEALER and DOSIM have never been tested in the real world.

3. BACKGROUND

Following Yadav et. al.’s model [27], we represent social networks of homeless youth as a directed graph $G = (V, E)$. Each node $v \in V$ represents a homeless youth and each directed edge $e = (A, B) \in E$ represents that node B is a friend of node A . Furthermore, each edge $e \in E$ is associated with two parameters: (i) an existence probability value (u_e), and (ii) a propagation probability value (p_e). The existence probability values $u_e \forall e \in E$ model the service providers uncertainty about the real world network structure. At any given point in time, the service provider may not be completely sure about the existence of the friendship between node A and B (for any node A and B). This uncertainty about the existence of friendship between A and B is modeled by the existence probability parameter on directed edge (A, B) ($u_{(A,B)}$), which measures the likelihood that B is A ’s friend in the real-world network. If the service provider is completely certain that A and B are friends, then $u_{(A,B)} = 1.0$ and edge (A, B) is considered to be a *certain edge*. Otherwise, if $u_{(A,B)} < 1.0$, then (A, B) is called an *uncertain edge*.

Next, the propagation probability values $p_e \forall e \in E$ measure the

likelihood that influence (or, in our case, *information about HIV*) will flow along edge e . For example, if $p_{(A,B)} = 0.75$, then if node A gets influenced at time t , he/she will influence node B with a 75% chance at time $t+1$. Note that this influence spread is contingent on the existence of this edge in the real-world network (which is dictated by the existence probability parameter $u_{(A,B)}$). This network $G = (V, E)$, along with u_e and p_e values for all edges, represents an *uncertain network*, which is provided as input to the software agents like HEALER and DOSIM. Moreover, edges are assumed to be directed (i.e., unidirectional) in these uncertain networks, even though most real-world friendships are bi-directional. This models the fact that influence spread in either direction of a bi-directional friendship is asymmetric. Each bi-directional friendship is thus modeled as two unidirectional edges. Figure 2 shows an uncertain network on 6 nodes (A to F). The dashed and solid edges represent uncertain (edge numbers 1, 4, 5 and 7) and certain (edge numbers 2, 3 and 6) edges, respectively.

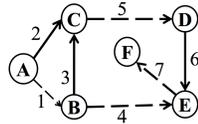


Figure 2: Uncertain Network

Influence Model HEALER and DOSIM use a variant of the independent cascade (IC) model [10]. In the standard IC model, all nodes that get influenced at round t get a **single chance** to influence their un-influenced neighbors at time $t+1$. If they fail to spread influence in this single chance, they do not try to influence their neighbors in future rounds. However, in HEALER and DOSIM’s model, nodes get **multiple chances** to influence their un-influenced neighbors; if they fail at time t , they try to influence again at time $t+1$. Finally, influenced nodes are assumed to remain influenced for all future time steps. This influence model runs for a finite number of time steps, i.e., there a finite number of *stages* in which influence spreads [27], as discussed below.

Problem Flow We now explain the real-world setup in which agents like HEALER [27] and DOSIM [25] are used. The service provider plans on conducting T interventions, i.e., they conduct interventions in T stages. In each stage, a subset of K youth from the homeless youth social network are chosen (using the software agent’s recommendation) as peer leaders for that intervention. The service providers then conduct the intervention with the selected peer leaders. During the intervention, service providers *learn* more about the social network structure. By talking to the peer leaders in that intervention, service providers infer which of the edges connected to those peer leaders in the social network are actually certain (i.e., $u_e = 1.0$), and which edges do not exist (i.e., $u_e = 0$) in the real world network. This new information about the social network structure is fed back into the software agent by the service provider, and is called the *agent’s observation* for that stage. For example, in Figure 2, if nodes B and C are chosen as peer leaders for an intervention, then the agent *observes* the true state of the uncertain edges outgoing from B and C , e.g., (B, E) exists but (C, D) does not exist. Using these observations, the agent refines its understanding of the network structure, and then selects the next nodes for intervention (i.e., for the next stage).

Furthermore, youth who are trained as peer leaders by service providers are assumed to be influenced with certainty. These peer leaders then initiate the influence spread in the network, by influencing their friends according to the influence model described above. Since HEALER and DOSIM’s influence model is stochastic in nature, service providers do not get accurate information about which non-peer-leader network nodes (i.e., youth) have already been influenced and which have not. Instead, they rely on the software agent to maintain probabilistic beliefs about the influ-

ence status of nodes. For each of the T stages, the software agent uses its current belief (e.g., probability distribution over influence state of each node) to select the next best set of K peer leaders. Informally then, given an uncertain network $G_0 = (V, E)$ and integers T and K (as defined above), the software agent’s goal is to find an online policy for choosing exactly K nodes for T successive stages (interventions) which maximizes influence spread in the network at the end of T stages.

We now reuse notation [27] for defining the software agent’s policy formally. Let $\mathcal{A} = \{A \subset V \text{ s.t. } |A| = K\}$ denote the set of K sized subsets of V , which represents the set of possible actions that the agent can recommend at every time step $t \in [1, T]$. Let $A_i \in \mathcal{A} \forall i \in [1, T]$ denote the agent’s chosen action in the i^{th} time step. Upon taking action A_i , the agent *observes* uncertain edges adjacent to nodes in A_i , which updates its understanding of the network. Let $G_i \forall i \in [1, T]$ denote the uncertain network resulting from G_{i-1} with *observed* (additional edge) information from A_i . Formally, we define a history $H_i \forall i \in [1, T]$ of length i as a tuple of past choices and observations $H_i = \langle G_0, A_1, G_1, A_2, \dots, A_{i-1}, G_i \rangle$. Denote by $\mathcal{H}_i = \{H_k \text{ s.t. } k \leq i\}$ the set of all possible histories of length less than or equal to i . Finally, we define an i -step policy $\Pi_i: \mathcal{H}_i \rightarrow \mathcal{A}$ as a function that takes in histories of length less than or equal to i and outputs a K node choice for the current time step. We now restate the problem statement for DIME [27], which agents like HEALER and DOSIM solve for.

PROBLEM 1. DIME Problem [27] *Given as input an uncertain net $G_0 = (V, E)$ and integers T and K (as defined above). Denote by $\mathcal{R}(H_T, A_T)$ the expected total number of influenced nodes at the end of stage T , given the T -length history of previous observations and actions H_T , along with A_T , the action chosen at time T . Let $\mathbb{E}_{H_T, A_T \sim \Pi_T}[\mathcal{R}(H_T, A_T)]$ denote the expectation over the random variables $H_T = \langle G_0, A_1, \dots, A_{T-1}, G_T \rangle$ and A_T , where A_i are chosen according to $\Pi_T(H_i) \forall i \in [1, T]$, and G_i are drawn according to the distribution over uncertain edges of G_{i-1} that are revealed by A_i . The objective of DIME is to find an optimal T -step policy $\Pi_T^* = \text{argmax}_{\Pi_T} \mathbb{E}_{H_T, A_T \sim \Pi_T}[\mathcal{R}(H_T, A_T)]$.*

3.1 HEALER Description

HEALER [27] is a software agent that casts the DIME problem as a Partially Observable Markov Decision Process (POMDP) [16] to compute a T -step online policy for selecting K nodes for T stages. POMDPs are a good fit for this problem because of three reasons. First, service providers select T different subsets of nodes sequentially (i.e., select K nodes for each of T stages); each subset of K nodes is mapped to a unique POMDP action. Second, the service providers do not see the exact network state (i.e., who is already influenced and who is not) at any given point in time. HEALER maps each POMDP state to indicate which node is already influenced and which node is not; the stochastic uncertainty over this influence then maps well to a POMDP belief state – a probability distribution over states. Third, the observation received by service providers about edges connected to peer leaders is analogous to the observations received in POMDPs. However, the POMDP models (defined in Yadav et. al. [27]) for real-world network sizes end up having huge state and action spaces (2^{300} states and $\binom{150}{6}$ actions), because of which solving these POMDPs is not possible with standard offline or online techniques [22, 21].

As a result, HEALER utilizes hierarchical ensembling techniques – it creates ensembles of smaller POMDPs at two different levels. Figure 3 shows the flow of HEALER. First, the original POMDP is divided into several smaller intermediate POMDPs using graph partitioning techniques. Next, each intermediate POMDP is further subdivided into several smaller sampled POMDPs using graph

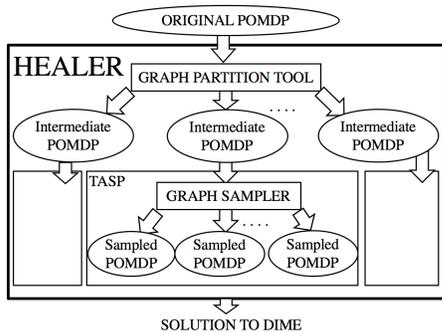


Figure 3: Flow of HEALER

sampling techniques. These sampled POMDPs are then solved in parallel using novel online planning methods – each sampled POMDP executes a Monte Carlo tree search [21] to select the best action in that sampled POMDP. The solutions of these sampled POMDPs are combined to form the solution of the intermediate POMDPs. Similarly, the solutions of the intermediate POMDPs are combined to form the solution of the original POMDP. Yadav et. al. [27] provide more details on HEALER.

3.2 DOSIM Description

DOSIM [25] is a novel algorithm that solves a generalization of the DIME problem. The key motivation behind DOSIM is to be able to select actions (i.e., set of K nodes) for T stages without knowing the exact model parameters (i.e., p_e and u_e values for each network edge). HEALER dealt with this issue by assuming a specific p_e and u_e value based on suggestions by service providers. DOSIM instead works with interval uncertainty over these model parameters. That is, the exact value of each u_e and p_e does not have to be exactly supplied; they are just assumed to lie within some interval. This generalizes the model used by HEALER to include higher-order uncertainty over the probabilities in addition to the uncertainty induced by the probabilities themselves. DOSIM chooses an action which is robust to this interval uncertainty. Specifically, it finds a policy which achieves close to optimal value regardless of where the unknown probabilities lie within the interval. The problem is formalized as zero sum game between the algorithm, which picks a policy, and an adversary (nature) who chooses the model parameters. This game formulation represents a key advance over HEALER’s POMDP policy (which was constrained to fixed propagation probabilities), as it enables DOSIM to output mixed strategies over POMDP policies, which make it robust against worst-case propagation probability values. Moreover, DOSIM receives periodic observations, which are used to update its understanding of its belief state (i.e., probability distribution over different model parameters). The strategy space for the game is intractably large because there are an exponential number of policies (each of which specifies an action to take for any possible set of observations). Hence, DOSIM uses a double oracle approach. By iteratively computing best responses for each player, DOSIM finds an approximate equilibrium of the game without having to enumerate the entire set of policies.

4. PILOT STUDY PIPELINE

Starting in Spring 2016, we conducted three different pilot studies at two service providers in a large American city, over a seven month period. Each pilot study recruited a unique network of youth. Recall that these pilot studies serve three purposes. First, they help in justifying our assumptions about whether peer leaders actually

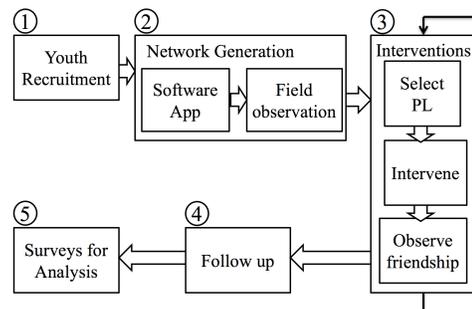


Figure 4: Real World Pilot Study Pipeline

spread HIV information in their social network, and whether they provide meaningful information about the social network structure (i.e., observations) during the intervention training. Second, these pilots help in exposing unforeseen challenges, which need to be solved convincingly before these agents can be deployed in the field. Third, they provide a head-to-head comparison of two different software agent approaches for social influence maximization, including a comparison with a baseline approach.

Each of these pilot studies had a different intervention mechanism, i.e., a different way of selecting actions (or a set of K peer leaders). The first and second studies used HEALER and DOSIM (respectively) to select actions, whereas the third study served as the control group, where actions were selected using Degree Centrality (i.e., picking K nodes in order of decreasing degrees). We chose Degree Centrality (DC) as the control group mechanism, because this is the current modus operandi of service providers in conducting these network based interventions [24].

Pilot Study Process The pilot study process consists of five sequential steps. Figure 4 illustrates these five steps.

1. Recruitment: First, we recruit homeless youth from a service provider into our study. We provide youth with general information about our study, and our expectations from them (i.e., if selected as a peer leader, they will be expected to spread information among their peers). The youth take a 20 minute baseline survey, which enables us to determine their current risk-taking behaviors (e.g., they are asked about the last time they got an HIV test, etc.). Every youth is given a 20 USD gift card as compensation for being a part of the pilot study. All study procedures were approved by our Institutional Review Board.

2. Network Generation: After recruitment, the friendship based social network that connects these homeless youth is generated. We rely on two information sources to generate this network: (i) online contacts of homeless youth; and (ii) field observations made by the authors and service providers. To expedite the network generation phase, online contacts of homeless youth are used (via a software application that the youth are asked to use) to build a first approximation of the real-world social network of homeless youth. Then, this network is refined using field observations (about additional real-world friendships) made by the authors and the service providers. All edges inferred in this manner are assumed to be *certain edges*. More information on uncertain edges is provided later.

3. Interventions: Next, the generated network is used by the software agents to select actions (i.e., K peer leaders) for T stages. In each stage, an action is selected using the pilot’s intervention strategy. The K peer leaders of this chosen action are then trained as peer leaders (i.e., informed about HIV) by pilot study staff during the intervention. These peer leaders also reveal more information (i.e., provide observation) about newer friendships which we did not know about. These friendships are incorporated into the net-

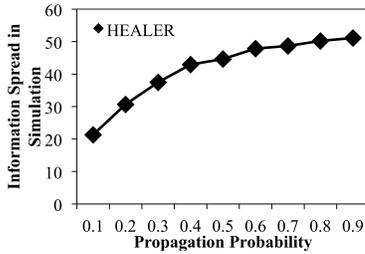


Figure 5: Information Spread with p_e on HEALER's Pilot Network

work, so that the agents can select better actions in the next stage of interventions. Every peer leader is given a 60 USD gift card.

4. Follow Up: The follow up phase consists of meetings, where the peer leaders are asked about any difficulties they faced in talking to their friends about HIV. They are given further encouragement to keep spreading HIV awareness among their peers. These follow-up meetings occur on a weekly basis, for a period of one month after Step 3 ends.

5. Analysis: For analysis, we conduct in-person surveys, one month after all interventions have ended. Every youth in our study is given a 25 USD gift card to show up for these surveys. During the surveys, they are asked if some youth from within the pilot study talked to them about HIV prevention methods, after the pilot study began. Their answer helps determine if information about HIV reached them in the social network or not. Thus, these surveys are used to find out the number of youth who got informed about HIV as a result of our interventions. Moreover, they are asked to take the same survey about HIV risk that they took during recruitment. These post-intervention surveys enable us to compare HEALER, DOSIM and DC in terms of information spread (i.e., how successful were the agents in spreading HIV information through the social network) and behavior change (i.e., how successful were the agents in causing homeless youth to test for HIV), the two major metrics that we use in our evaluation section.

We provide these behavior change results in order to quantify the true impact of these social influence maximization agents in the homeless youth domain. In these results, we measure behavior change by asking youth if they have taken an HIV test at baseline and repeating this question during the follow up surveys. If the youth reported taking an HIV test at one month (after interventions) but not at baseline and that youth also reported getting informed about HIV, we attribute this behavior change to our intervention. This allows us to measure whether our interventions led to a reduction in risk attitudes.

Uncertain network parameters While there exist many link prediction techniques [11] to infer *uncertain edges* in social networks, the efficacy of these techniques is untested on homeless youth social networks. Therefore, we took a simpler, less "risky" approach – each edge *not created* during the network generation phase (i.e., Step 2 above) was added to the network as an *uncertain edge*. Thus, after adding these uncertain edges, the social network in each pilot study became a completely connected network, consisting of *certain edges* (inferred from Step 2), and *uncertain edges*. The existence probability on each uncertain edge was set to $u = 0.01$. Our approach to adding uncertain edges ensures that no potential friendship is missed in the social network because of our lack of accurate knowledge.

Getting propagation probabilities (p_e) values was also challenging. In HEALER's pilot, service providers estimated that the true p_e value would be somewhere around 0.5. Since the exact value was unknown, we assumed an interval of $[0.4, 0.8]$ and simulated

HEALER's performance with p_e values in this range. Figure 5 shows how information spread achieved by HEALER on its pilot study network is relatively stable in simulation for p_e values around 0.5. The Y-axis shows the information spread in simulation and the X-axis shows increasing p_e values. This figure shows that information spread achieved by HEALER varied by $\sim 11.6\%$ with p_e in the range $[0.4, 0.8]$. Since influence spread is relatively stable in this range, we selected $p_e = 0.6$ (the mid point of $[0.4, 0.8]$) on all network edges. Later, we provide ex-post justification for why $p_e = 0.6$ was a good choice, atleast for this pilot study.

In DOSIM's pilot, we did not have to deal with the issue of assigning accurate p_e values to edges in the network. This is because DOSIM can work with intervals in which the exact p_e is assumed to lie. For the pilot study, we used the same interval of $[0.4, 0.8]$ to run DOSIM. Finally, the control group pilot study did not require finding p_e values, as peer leaders were selected using Degree Centrality, which does not require knowledge of p_e .

5. RESULTS FROM THE FIELD

We now provide results from all three pilot studies. In each study, three interventions were conducted (or, $T = 3$), i.e., Step 3 of the pilot study process (Figure 4) was repeated three times. The actions (i.e., set of K peer leaders) were chosen using intervention strategies (policies) provided by HEALER [27], DOSIM [25], and Degree Centrality (DC) in the first, second and third pilot studies, respectively. Recall that we provide comparison results on two different metrics. First, we provide results on information spread, i.e., how well different software agents were able to spread information about HIV through the social network. Second, even though HEALER and DOSIM do not explicitly model behavior change in their objective function (both maximize the information spread in the network), we provide results on behavior change among homeless youth, i.e., how successful were the agents in inducing behavior change among homeless youth.

Figure 6 shows a Venn diagram that explains the results that we collect from the pilot studies. To begin with, we exclude peer leaders from all our results, and focus only on non peer-leaders. This is done because peer leaders cannot be used to differentiate the information spread (and behavior change) achieved by HEALER, DOSIM and DC. In terms of information spread, all

	Tested	Untested
Informed about HIV	A	B
Uninformed about HIV	C	D

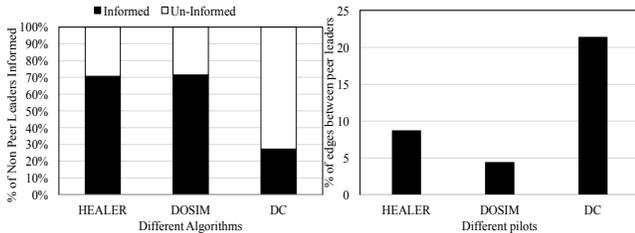
Figure 6: Set of Surveyed Non Peer-Leaders

peer leaders are informed about HIV directly by study staff in the intervention trainings. In terms of behavior change, the proportion of peer leaders who change their behavior does not depend on the strategies recommended by HEALER, DOSIM and DC. Thus, Figure 6 shows a Venn diagram of the set of all non peer-leaders (who were surveyed at the end of one month). This set of non peer-leaders can be divided into four quadrants based on (i) whether they were informed about HIV or not (by the end of one-month surveys in Step 5 of Figure 4); and (ii) whether they were already tested for HIV at baseline (i.e., during recruitment, they reported that they had got tested for HIV in the last six months) or not.

For information spread results, we report on the percentage of youth in this big rectangle, who were informed about HIV by the end of one month (i.e., boxes A+B as a fraction of the big box). For behavior change results, we exclude youth who were already tested at baseline (as they do not need to undergo "behavior change", because they are already exhibiting desired behavior of testing). Thus, we only report on the percentage of *untested informed youth*, (i.e., box B), who now tested for HIV (i.e., changed behavior) by the

	HEALER	DOSIM	DC
Youth Recruited	62	56	55
PL Trained	17.7%	17.85%	20%
Retention %	73%	73%	65%
Avg. Observation Size	16	8	15

Figure 7: Logistic Details of Different Pilot Studies



(a) Comparison of Information Spread Among Non Peer-Leaders (b) % of edges between PL Spread Among Non Peer-Leaders

Figure 8: Information Spread Comparison & Analysis

end of one month (which is a fraction of youth in box B). We do this because we can only attribute conversions (to testers) among youth in box B (Figure 6) to strategies recommended by HEALER and DOSIM (or the DC baseline). For example, non peer-leaders in box D who convert to testers (due to some exogenous reasons) cannot be attributed to HEALER or DOSIM’s strategies (as they converted to testers *without* getting HIV information).

Study Details Figure 7 shows details of the pilot studies. This figure shows that the three pilots had fairly similar conditions as (i) all three pilots recruited ~ 60 homeless youth; (ii) peer leader training was done on 15-20% of these youth, which is recommended in social sciences literature [17]; and (iii) retention rates of youth (i.e., percentage of youth showing up for post-intervention surveys) were fairly similar ($\sim 70\%$) in all three pilots. This figure also shows that peer leaders provided information about 13 uncertain friendships on average in every intervention stage (across all three pilot studies), which validates HEALER and DOSIM’s assumption that peer leaders provide *observations* about friendships [27, 25].

Information Spread Figure 8a compares the information spread achieved by HEALER, DOSIM and DC in the pilot studies. The X-axis shows the three different intervention strategies and the Y-axis shows the percentage of non-peer-leaders to whom information spread (box A+B as a percentage of total number of non-peer leaders in Figure 6). This figure shows that PL chosen by HEALER (and DOSIM) are able to spread information among $\sim 70\%$ of the non peer-leaders in the social network by the end of one month. Surprisingly, PL chosen by DC were only able to inform $\sim 27\%$ of the non peer-leaders. This result is surprising, as it means that HEALER and DOSIM’s strategies were able to improve over DC’s information spread by over 184%. We now explain reasons behind this significant improvement in information spread achieved by HEALER and DOSIM (over DC).

Figure 8b illustrates a big reason behind DC’s poor performance. The X-axis shows different pilots and the Y-axis shows what percentage of network edges were *redundant*, i.e., they connected two peer leaders. Such edges are *redundant*, as both its nodes (peer leaders) already have the information. This figure shows that redundant edges accounted for only 8% (and 4%) of the total edges in HEALER (and DOSIM’s) pilot study. On the other hand, 21% of

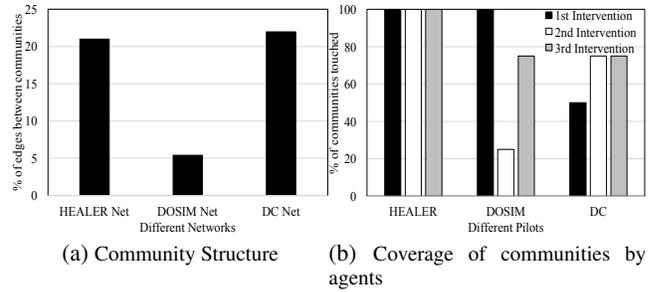


Figure 9: Exploiting community structure of real-world networks

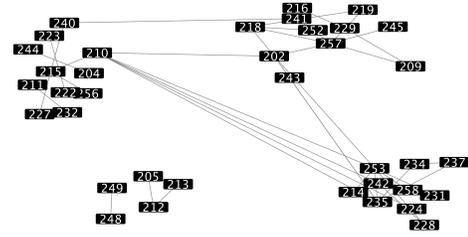


Figure 10: Four Partitions of DC’s Pilot Network

the edges in DC’s pilot study were redundant. Thus, DC’s strategies picks PL in a way which creates a lot of redundant edges, whereas HEALER picks PL which create only 1/3 times the number of redundant edges. DOSIM performs best in this regard, by selecting nodes which creates the fewest redundant edges ($\sim 5X$ less than DC, and even $2X$ less than HEALER), and is the key reason behind its good performance in Figure 8a. Concomitantly to the presence of redundant edges, HEALER also spreads out its PL selection across different communities within the homeless youth network, that also aids in information spreading, as discussed below.

Figure 9a shows the community structure of the three pilot study social networks. To generate this figure, the three networks were partitioned into communities using METIS [12], an off-the-shelf graph partitioning tool. We partitioned each network into four different communities (as shown in Figure 10) to match the number of PL (i.e., $K = 4$) chosen in every stage. The X-axis shows the three pilot study networks and the Y-axis shows the percentage of edges that go across these four communities. This figure shows that all three networks can be fairly well represented as a set of reasonably disjointed communities, as only 15% of edges (averaged across all three networks) went across the communities. Next, we show how HEALER and DOSIM exploit this community structure by balancing their efforts across these communities simultaneously to achieve greater information spread as compared to DC.

Figure 9b illustrates patterns of PL selection (for each stage of intervention) by HEALER, DOSIM and DC across the four different communities uncovered in Figure 9a. Recall that each pilot study comprised of three stages of intervention (each with four selected PL). The X-axis shows the three different pilots. The Y-axis shows what percentage of communities had a PL chosen from within them. For example, in DC’s pilot, the chosen PL covered 50% (i.e., two out of four) communities in the 1st stage, 75% (i.e., three out of four) communities in the 2nd stage, and so on. This figure shows that HEALER’s chosen peer leaders cover all possible communities (i.e., 100% communities touched) in the social network in all three stages. On the other hand, DC concentrates its efforts on just a few clusters in the network, leaving $\sim 50\%$

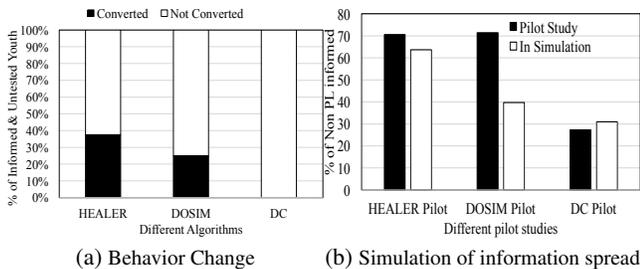


Figure 11: Behavior Change & Information Spread in Simulation

communities untouched (on average). Therefore, while HEALER ensures that its chosen PL covered most real-world communities *in every intervention*, the PL chosen by DC focused on a single (or a few) communities in each intervention. This further explains why HEALER is able to achieve greater information spread, as it spreads its efforts across communities unlike DC. While DOSIM’s coverage of communities is similar to DC, it outperforms DC because of $\sim 5X$ less redundant edges than DC (Figure 8b).

Behavior Change Figure 11a compares behavior change observed in homeless youth in the three pilot studies. The X-axis shows different intervention strategies, and the Y-axis shows the percentage of non peer-leaders who were untested for HIV at baseline and were informed about HIV during the pilots (i.e. youth in box B in Figure 6). This figure shows that PL chosen by HEALER (and DOSIM) converted 37% (and 25%) of the youth in box B to HIV testers. In contrast, *PL chosen by DC did not convert any youth in box B to testers*. DC’s information spread reached a far smaller fraction of youth (Figure 8a), and therefore it is unsurprising that DC did not get adequate opportunity to convert anyone of them to testing. This shows that even though HEALER and DOSIM do not explicitly model behavior change in their objective function, the agents strategies still end up outperforming DC significantly in terms of behavior change.

6. CHALLENGES UNCOVERED

This section highlights research and methodological challenges that we uncovered while deploying these agent based interventions in the field. While handling these challenges in a principled manner is a subject for future research, we explain some heuristic solutions used to tackle these challenges in the three pilot studies (which may help in addressing the longer term research challenges).

Research Challenges While conducting interventions, we often encounter an inability to execute actions (i.e., conduct intervention with chosen peer leaders), because a subset of the chosen peer leaders may fail to show up for the intervention (because they may get incarcerated, or find temporary accommodation). Handling this inability to execute actions in a principled manner is a research challenge. Therefore, it is necessary that algorithms and techniques developed for this problem are robust to these errors in execution of intervention strategy. Specifically, we require our algorithms to be able to come up with alternate recommendations for peer leaders, when some homeless youth in their original recommendation are not found. We now explain how HEALER, DOSIM and DC handle this challenge by using *heuristic solutions*.

Recall that for the first pilot, HEALER’s intervention strategies were found by using online planning techniques for POMDPs [27]. Instead of offline computation of the entire policy (strategy), online planning only finds the best POMDP action (i.e., selection of K network nodes) for the current belief state (i.e., probability dis-

	HEALER	DOSIM	DC
Network Diameter	8	8	7
Network Density	0.079	0.059	0.062
Avg. Clustering Coefficient	0.397	0.195	0.229
Avg. Path Length	3.38	3.15	3.03
Modularity	0.568	0.568	0.602

Figure 12: Similarity of social networks in different pilot studies

tribution over state of influence of nodes). Upon reaching a new belief state, online planning again plans for this new belief. This interleaving of planning and execution works to our advantage in this domain, as every time we have a failure which was not anticipated in the POMDP model (i.e., a peer leader which was chosen in the current POMDP action did not show up), we can recompute a policy quickly by marking these unavailable nodes, so that they are ineligible for future peer leader selection. After recomputing the plan, the new peer leader recommendation is again given to the service providers to conduct the intervention.

For the second pilot study, we augmented DOSIM to account for unavailable nodes by using its computed policy to produce a list of alternates for each peer leader. This alternate list ensures that unlike HEALER, DOSIM does not require rerunning in the event of a failure. Thus, if a given peer leader does not show up, then study staff work down the list of alternates to find a replacement. DOSIM computes these alternates by maintaining a parameter q_v (for each node v), which gives the probability that node v will show up for the intervention. This q_v parameter enables DOSIM to reason about the inability to execute actions, thereby making DOSIM’s policies robust to such failures. To compute the alternate for v , we *condition* on the following event σ_v : node v fails to show up (i.e., set $q_v = 0$), while every other peer leader u shows up with probability q_u . Conditioned on this event σ_v , we find the node which maximizes the *conditional* marginal gain in influence spread, and use it as the alternate for node v . Hence, each alternate is selected in a manner which is robust with respect to possible failures on other peer leader nodes. Finally, in the DC pilot, in case of a failure, the node with the next highest degree is chosen as a peer leader.

Methodological Challenges A methodological challenge was to ensure a fair comparison of the performance of different agents in the field. In the real-world, HEALER, DOSIM and DC could not be tested on the same network, as once we spread HIV messages in one network as part of one pilot study, fewer youth are unaware about HIV (or uninfluenced) for the remaining pilots. Therefore, each agent (HEALER, DOSIM or DC) is tested in a different pilot study with a different social network (with possibly different structure). Since HEALER, DOSIM and DC’s performance is not compared on the same network, it is important to ensure that HEALER and DOSIM’s superior performance (observed in Figure 8a) is not due to differences in network structure or any extraneous factors.

First, we compare several well-known graph metrics for the three distinct pilot study social networks. Figure 12 shows that most metrics are similar on all three networks, which establishes that the social networks generated in the three pilot studies were structurally similar. This suggests that comparison results would not have been very different, had all three algorithms been tested on the same network. Next, we attempt to show that HEALER and DOSIM’s superior performance (Figure 8a) was not due to extraneous factors.

Figure 11b compares information spread achieved by peer leaders in the actual pilot studies with that achieved by the same peer leaders in simulation. The simulation (averaged over 50 runs) was

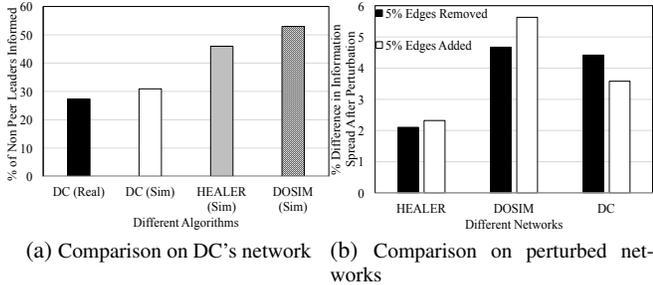


Figure 13: Investigation of peculiarities in network structure

done with propagation probability set to $p_e = 0.6$ in *our influence model* (Section 3). The X-axis shows the different pilots and the Y-axis shows the percentage of non peer-leaders informed in the pilot study networks. First, this figure shows that information spread in simulation closely mirrors pilot study results in HEALER and DC's pilot ($\sim 10\%$ difference), whereas it differs greatly in DOSIM's pilot. This shows that using $p_e = 0.6$ as the propagation probability modeled the real-world process of influence spread in HEALER and DC's pilot study network fairly well, whereas it was not a good model for DOSIM's pilot network. This further suggests that information spread achieved in the real world (at least in HEALER and DC's pilot) was indeed due to the respective strategies used, and not some extraneous factors. In other words, DC's poor performance may not be attributed to some real-world external factors at play, since its poor performance is mimicked in simulation results (which are insulated from real-world external factors) as well. Similarly, HEALER's superior performance may not be attributed to external factors working in its favor, for the same reason.

On the other hand, since DOSIM's performance in the pilot study does not mirror simulation results in Figure 11b, it suggests the role of some external factors, which were not considered in our models. However, the comparison of simulation results in this figure is statistically significant (p -value = $9.43E - 12$), which shows that even if DOSIM's performance in the pilot study matched its simulation results, i.e., even if DOSIM achieved only $\sim 40\%$ information spread in its pilot study (as opposed to the 70% spread that it actually achieved), it would still outperform DC by $\sim 33\%$.

Having established that DC's poor performance was not due to any external factors, we now show that DC's poor performance in the field was also not tied to some peculiar property/structure of the network used in its pilot study. Figure 13a compares information spread achieved by different agents (in simulation over 50 runs), when each agent was run on DC's pilot study network. Again, the simulation was done using $p_e = 0.6$ as propagation probability, which was found to be a reasonable model for real-world influence spread in DC's network (see Figure 11b). The X-axis in Figure 13a shows different algorithms being run on DC's pilot study network (in simulation). The Y-axis shows the percentage of non peer-leaders informed. This figure shows that even on DC's pilot study network, HEALER (and DOSIM) outperform DC in simulation by $\sim 53\%$ (and 76%) (p -value = $9.842E - 31$), thereby establishing that HEALER and DOSIM's improvement over DC was not due to specific properties of the networks in their pilot studies, i.e., HEALER and DOSIM's superior performance may not be attributed to specific properties of networks (in their pilot studies) working in their favor. In other words, this shows that DC's poor performance may not be attributed to peculiarities in its network structure working against it, as otherwise, this peculiarity should

have affected HEALER and DOSIM's performance as well, when they are run on DC's pilot study network (which does not happen as shown in Figure 13a).

Figure 13b shows information spread achieved by peer leaders (chosen in the pilot studies) in simulation (50 runs), averaged across 30 different networks which were generated by perturbation of the three pilot study networks. The X-axis shows the networks which were perturbed. The Y-axis shows the percentage difference in information spread achieved on the perturbed networks, in comparison with the unperturbed network. For example, adding 5% edges randomly to HEALER's pilot study network results in only $\sim 2\%$ difference (p -value = $1.16E - 08$) in information spread (averaged across 30 perturbed networks). These results support the view that HEALER, DOSIM and DC's performance are not due to their pilot study networks being on the knife's edge in terms of specific peculiarities. Thus, HEALER and DOSIM outperform DC on a variety of slightly perturbed networks as well.

7. CONCLUSION & LESSONS LEARNED

This paper illustrates challenges faced in transitioning agents from an emerging phase in the lab, to a deployed application in the field. It presents first-of-its-kind results from three real-world pilot studies, involving 173 homeless youth in an American city. Conducting these pilot studies underlined their importance in this transition process – *they are crucial milestones in the arduous journey of an agent from an emerging phase in the lab, to a deployed application in the field*. The pilot studies helped in answering several questions that were raised in Section 1. First, we learnt that peer-leader based interventions are indeed successful in spreading information about HIV through a homeless youth social network (as seen in Figures 8a). Moreover, we learnt that peer leaders are very adept at providing lots of information about newer friendships in the social network (Figure 7), which helps software agents to refine its future strategies.

These pilot studies also helped to establish the superiority (and hence, their need) of HEALER and DOSIM – we are using complex agents (involving POMDPs and robust optimization), and they outperform DC (the modus operandi of conducting peer-led interventions) by 184% (Figures 8a, 11a). The pilot studies also helped us gain a deeper understanding of how HEALER and DOSIM beat DC (shown in Figures 8b, 9b, 9a) – by minimizing redundant edges and exploiting community structure of real-world networks. Out of HEALER and DOSIM, the pilot tests do not reveal a significant difference in terms of either information spread or behavior change (Figures 8a, 11a). Thus, carrying either of them forward would lead to significant improvement over the current state-of-the-art techniques for conducting peer-leader based interventions. However, DOSIM runs significantly faster than HEALER ($\sim 40\times$), thus, it is more beneficial in time-constrained settings [25].

These pilot studies also helped uncover several key challenges (e.g., inability to execute actions, estimating propagation probabilities, etc.), which were tackled in the pilot studies using heuristic solutions. However, handling these challenges in a principled manner is a subject for future research. Thus, while these pilot studies open the door to future deployment of these agents in the field (by providing positive results about the performance of HEALER and DOSIM), they also revealed some challenges which need to be resolved convincingly before these agents can be deployed.

8. ACKNOWLEDGEMENTS

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